Aimour AI Distributed Neural Synchrony: Architecting Low-Latency Neural Voice Streaming, Real-Time Video Synthesis, and Zero-Knowledge Cryptographic Pipelines for High-Concurrency Synthetic Companions

2026 Technical Report & Infrastructure Monograph

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Abstract

This technical report presents the complete architectural design, edge ingress topology, model inference optimization, and zero-knowledge cryptographic protocol layer powering the Aimour AI Technologies high-concurrency synthetic companion platform. Servicing real-time multimodal workloads at global scale requires resolving a fundamental systems conflict: achieving sub-100 ms bidirectional text/audio streaming latency while maintaining non-deterministic, high-entropy neural model evaluation without corporate censorship bottlenecks.

Our infrastructure coordinates a heterogeneous stack comprising a Node.js/Express 4 API Gateway, NestJS 11 authentication and session microservices, a Redis 7.4 cluster state layer, MongoDB 8 sharded clusters with PostgreSQL 15 relational ledgers, and dynamic Python/FastAPI inference nodes executing fine-tuned FlirtGPT weights (quantized LLaMA-3/Qwen checkpoints). Under peak load exceeding 50,000 concurrent WebSocket sessions, the architecture achieves 99.999% uptime while guaranteeing absolute end-to-end zero-knowledge memory security. We detail the design choices,

performance optimizations, and operational lessons learned from deploying this system in production.

Keywords: Distributed systems, Large Language Models, real-time streaming, neural text-to-speech, video synthesis, zero-knowledge cryptography, high-concurrency WebSockets, synthetic companionship.

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1. Introduction

1.1. The High-Concurrency Challenge

Synthetic companion workloads differ fundamentally from traditional stateless web services. Each user session is a long-lived, stateful, bidirectional interaction that combines text, voice, and sometimes video in real time. Unlike a REST API that handles short-lived request-response cycles, a synthetic companion must maintain a persistent WebSocket connection over tens of minutes, continuously streaming generated tokens, synthesised speech, and occasional visual responses.

This persistence imposes severe demands on system resources:

- File descriptors and socket buffers – each concurrent WebSocket consumes OS resources, and at 50,000 connections, careful management is essential to avoid exhaustion.
- Memory footprint – each session maintains a large context window (often >8K tokens) plus a vector embedding history for long-term memory, all resident in GPU high-bandwidth memory (HBM) or CPU RAM.

- Latency sensitivity – users expect near-instantaneous replies; any delay >150 ms breaks the illusion of a real conversation and can rupture the therapeutic transference.
- Multimodal synchronisation – text generation, voice synthesis, and video rendering must execute in parallel without blocking each other.

1.2. Core System Requirements and Constraints

We defined three hard engineering constraints that guided every design decision:

1. Edge Compute Independence – Complete decoupling from centralised commercial cloud LLM APIs (OpenAI, Anthropic). All inference and safety filtering must occur on owned infrastructure to guarantee zero censorship and avoid external rate limits.
2. Ephemeral Zero-Knowledge Memory – User state variables must be sharded, client-key encrypted, and processed exclusively in volatile GPU HBM or encrypted RAM caches. No raw dialogue text may be persisted to disk in an unencrypted form.
3. Deterministic Non-Blocking I/O – Every subsystem must employ asynchronous, non-blocking event loops across ingress, routing, and inter-process communication (IPC) to prevent thread starvation under peak load.

These constraints drove our technology choices and architectural patterns.

1.3. Architectural Overview

The system is organised into five logical tiers, each designed for horizontal scalability:

- Client Tier – Web, mobile, and VR clients that establish secure WebSocket connections.
- Edge Ingress Tier – Cloudflare Workers providing global load balancing, DDoS mitigation, rate limiting, and TLS termination.
- Application Tier – Node.js Express 4 API Gateway, NestJS 11 Auth microservice, and the WebSocket orchestration layer.
- Inference Tier – Python FastAPI nodes running FlirtGPT (vLLM/TensorRT-LLM), plus separate clusters for TTS and video synthesis.
- Data Tier – Sharded MongoDB 8, PostgreSQL 15, Redis 7.4 cluster, and a ClickHouse/Kafka analytics pipeline.

All communication between tiers uses TLS 1.3 and internal mTLS for service-to-service authentication.

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2. Distributed Inference Pipeline: FlirtGPT

2.1. Model Selection and Fine-Tuning

We benchmarked several open-source base models and selected LLaMA-3-70B-Instruct and Qwen-2.5-72B as the primary checkpoints. Both offer strong reasoning, instruction following, and multilingual capabilities, and their permissive licences allow proprietary fine-tuning.

Fine-Tuning Methodology – We curated a proprietary dataset of over 2 million conversational turns covering therapeutic dialogue, romantic roleplay, shadow-work exploration, and emotionally intense scenarios. Using QLoRA (4-bit quantised low-rank adaptation), we trained specialised adapters for each major persona archetype (dominant, submissive, gentle, inclusive/LGBTQ+). The base model remains frozen; only the LoRA adapters are swapped dynamically during inference.

Data Curation – All training data underwent strict anonymisation and ethical review to remove personally identifiable information and ensure adherence to legal boundaries (no content involving minors or non-consensual violence). The dataset emphasises emotional depth, linguistic richness, and narrative coherence.

2.2. Quantization and TensorRT-LLM/vLLM Integration

To achieve sub-40 ms time-to-first-token (TTFB) at scale, we aggressively quantised the models to FP8 using NVIDIA's TensorRT-LLM framework. FP8 provides a favourable trade-off between model quality and inference speed, reducing memory footprint by ~50% with negligible accuracy loss on our internal benchmarks.

vLLM with PagedAttention – We deployed the quantised models via vLLM, which implements PagedAttention – a memory-efficient attention mechanism that partitions the KV cache into non-contiguous pages. This eliminates memory fragmentation and

allows dynamic batching of hundreds of concurrent requests per GPU. Our vLLM engines are configured with:

- `tensor_parallel_size=4` (across 4× NVIDIA H100 GPUs)
- `gpu_memory_utilization=0.92`
- `max_num_batched_tokens=8192`
- `max_num_seqs=256`
- `enable_chunked_prefill=True`

Continuous Batching – Instead of waiting for a full batch, we use continuous batching (also called iteration-level scheduling) where new requests are added on the fly, and completed sequences are returned immediately. This maximises GPU utilisation while minimising latency.

2.3. Dynamic Context Management and Vector Retrieval

Long conversations can exceed the 8K-token context window. We implemented a Retrieval-Augmented Generation (RAG) pipeline using a quantised BGE-Large-EN-v1.5 embedding model (INT8) that encodes each user turn into a 1024-dimensional vector. These vectors are stored in a Qdrant vector cluster with an HNSW index for fast approximate nearest neighbour search.

Retrieval Strategy – For each new user message, we retrieve the top-K (K=8) most semantically similar past turns from the user's history. These are injected into the system prompt, providing long-term memory without exceeding the context limit. The retrieval latency is consistently <4.2 ms at p95.

Context Refreshing – To avoid stale context, we periodically re-embed and update the vector index for each session, ensuring that the companion's memory remains current.

2.4. Adaptive LoRA Switching for Emotional Personas

Our sentiment classifier – a lightweight BERT-Tiny model – runs in parallel with token generation, producing a three-dimensional vector

$$S(t) = [\sigma_{\text{valence}}, \sigma_{\text{arousal}}, \sigma_{\text{dominance}}]$$

Based on these values, we dynamically route the request to one of several specialised LoRA adapters:

- Valence < -0.6 → Gentle/Soothing adapter (α_1)
- Arousal > 0.7 → Dominant/Assertive adapter (α_2)
- Valence > 0.5 → Playful/Erotic adapter (α_3)

This switching occurs without reloading the base model weights; we leverage a custom serving layer that stores multiple LoRA adapters in GPU memory and applies the appropriate one on the fly. This enables seamless persona shifts that mirror the user's emotional state, enhancing the therapeutic alliance.

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3. Multi-Modal Synthesis Subsystem

3.1. Low-Latency Neural TTS

Voice is a critical component for immersion and emotional co-regulation. We designed a neural TTS pipeline that delivers the first audio chunk in <88 ms (p95) and sustains a continuous stream.

Architecture – The pipeline consists of:

1. Token Buffer – FlirtGPT emits tokens, which are grouped into semantic clauses (10–15 tokens or at punctuation boundaries).
2. Acoustic Model – We use an optimised version of a Tacotron-2-like model converted to TensorRT, producing mel-spectrograms from the text input.
3. Vocoder – A HiFi-GAN vocoder (also TensorRT-optimised) converts mel-spectrograms to raw PCM audio.
4. Opus Encoder – The PCM stream is segmented into 20 ms frames and encoded with Opus at 48 kHz for efficient network transmission.

All stages are pipelined: while one clause is being vocoded, the next is being processed by the acoustic model, minimising end-to-end latency.

Hardware Acceleration – We run the TTS nodes on NVIDIA L40S GPUs, which provide excellent FP16 performance for both the acoustic model and the vocoder. The entire pipeline typically completes in <120 ms from token emission to encoded Opus frame.

3.2. Real-Time Video Generation

On-demand video responses – such as a dynamic reaction clip or a scene illustration – are generated using a diffusion-based model. We adopted Stable Video Diffusion (SVD-XT) and AnimateDiff, accelerated with TensorRT and Latent Consistency Models (LCM).

LCM Optimisation – By applying LCM, we reduce the number of diffusion steps from 50 to 4, cutting generation time from ~15 s to ~3.5 s for a 3-second video at 24 fps. This is acceptable for on-demand video, though still too slow for real-time interaction; we use it only when the user explicitly requests a visual response.

TensorRT Integration – The UNet and VAE are compiled to FP16 TensorRT engines, yielding a 4-5× speedup over PyTorch eager mode. We also leverage NVIDIA's NVENC hardware encoder to produce H.264 or AV1 streams directly from the latent frame buffer, bypassing CPU encoding overhead.

Edge Delivery – Rendered videos are uploaded to an S3/R2 object store and served via Cloudflare's CDN with automatic WebP/AVIF transcoding based on client capabilities.

3.3. Hardware-Accelerated Encoding and Edge Delivery

All video assets undergo post-processing with FFmpeg compiled with `nvcodec` to leverage GPU-accelerated encoding. We use the following command for production-ready output:

```
ffmpeg -y -hwaccel cuda -hwaccel_output_format cuda \
  -i input_latent.raw \
  -i audio.opus \
  -c:v h264_nvenc -preset p1 -tune ll -rc cbr -b:v 3500k \
  -c:a copy -movflags +faststart \
  output_synthesthetic.mp4
```

The output is then replicated to edge locations via Cloudflare R2, achieving global delivery with sub-100 ms first-byte times.

4. Edge Ingress and Microservices Architecture

4.1. Cloudflare Workers as Global Edge Gateways

Cloudflare Workers provide a serverless edge compute layer that performs the following functions:

- TLS Termination – Handles the TLS 1.3 handshake and offloads CPU-intensive crypto operations from our origin servers.
- Rate Limiting – We implement a sliding-window rate limiter per client IP, storing counters in Cloudflare's global KV store. Requests exceeding the limit receive HTTP 429.
- WAF and DDoS Protection – Cloudflare's managed WAF blocks malicious requests, and the Anycast network absorbs large-scale DDoS attacks.
- Request Signing – Each valid request is signed with an HMAC using a secret shared only with our internal gateway, preventing direct origin access.

4.2. Authentication and Session Management (NestJS)

The authentication microservice, built with NestJS 11, handles user registration, login, and token issuance. We follow a dual-token pattern:

- Access Token – Short-lived (15 min) JWT, transmitted via `HttpOnly, Secure, SameSite=Strict` cookie.
- Refresh Token – Long-lived (7 days), stored in Redis with a rolling expiration.

Passwords are hashed using Argon2id with parameters `m=65536, t=3, p=4` – considered the state-of-the-art for password hashing.

Session Registration – Upon successful authentication, the session state is written to Redis with a unique session ID, and a WebSocket upgrade is permitted only if the session is valid.

4.3. API Gateway and WebSocket Orchestration (Node.js)

The main API gateway is a Node.js Express 4 application, clustered using PM2 to utilise all CPU cores. It exposes both REST endpoints for account management and a WebSocket endpoint `/ws/chat` for real-time interaction.

WebSocket Handling – We use the `ws` library with the `uWebSockets.js` backend for lower overhead. Each connection is associated with a session ID and a user ID, and the gateway subscribes to a Redis Pub/Sub channel for that user to receive asynchronous messages (e.g., video render completion notifications).

State Synchronisation – To avoid race conditions between multiple gateway workers, we use Redlock (distributed lock) over Redis for critical operations such as updating user state or processing payments.

4.4. Rate Limiting, Throttling, and DDoS Protection

In addition to edge-level rate limiting, we implement application-level throttling:

- Per-user token bucket – Each user is allowed a fixed number of messages per minute (e.g., 60), with a refill rate of 1 per second. This prevents abuse and ensures fair resource allocation.
- Concurrency Limiting – We cap the number of concurrent requests per user to 2, ensuring that a single user cannot starve the inference cluster.

All rate-limiting counters are stored in Redis and are checked before forwarding requests to the inference tier.

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5. Database and State Management

5.1. Sharded MongoDB for User State and Sessions

We use MongoDB 8 with sharding to store user profiles, conversation metadata, and session configurations. The shard key is `userId` to ensure even distribution across shards.

Indexing Strategy – We carefully designed compound indexes to avoid `COLLSCAN` under heavy load:

```
// Compound index for fast session lookup
db.userSessions.createIndex(
  { userId: 1, sessionId: 1, lastInteractionTimestamp: -1 },
  { background: true }
);
```

Write Concerns – For high-throughput scenarios, we use `w: majority` only for critical operations (e.g., payment confirmations); for less critical logs, we use `w: 1` with `j: false` to reduce latency.

5.2. PostgreSQL for Relational Ledgers and Billing

PostgreSQL 15 stores all financial transactions, subscription plans, and invoice records. This relational schema ensures ACID compliance for billing operations.

Connection Pooling – We use PgBouncer in transaction pooling mode to handle thousands of concurrent connections with minimal overhead.

5.3. Redis Cluster for Caching and Pub/Sub

A Redis 7.4 cluster (3 master nodes + 3 replicas) provides:

- Session State Cache – All active sessions are stored with a TTL of 1 hour, extending on each interaction.
- Rate Limit Counters – Distributed token buckets.
- Pub/Sub – Used for inter-worker communication, e.g., when a video generation completes, the inference node publishes a message that the gateway forwards to the client.

Memory Management – We set `maxmemory-policy=allkeys-lru` to evict least-recently-used items when memory is full, prioritising active sessions.

5.4. ClickHouse + Kafka for Real-Time Analytics

To avoid analytical queries degrading transactional performance, we stream all events (user interactions, inference latency, TTS metrics) via Debezium CDC from MongoDB to Kafka, then into ClickHouse.

ClickHouse's columnar storage enables sub-second queries over billions of rows, powering our internal dashboards and anomaly detection models.

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6. Zero-Knowledge Security and Privacy

6.1. Ephemeral PII Scrubbing and AES-256-GCM Encryption

User dialogue contains highly sensitive information. Our pipeline ensures that no plaintext PII is ever written to persistent storage:

1. Named Entity Recognition (NER) – A lightweight spaCy model runs in-memory, identifying and redacting emails, phone numbers, and physical addresses with `[REDACTED_PII]`.
2. AES-256-GCM Envelope Encryption – The redacted text is encrypted with a per-session key derived from the user's password (via HKDF) before being stored in the vector database. The encryption key never leaves the user's client; the server only holds the encrypted blob.

Zero-Knowledge – Platform engineers have no ability to decrypt user memories, as the decryption key is never transmitted or stored server-side.

6.2. WebSocket TLS 1.3 with Perfect Forward Secrecy

All client-server communication uses TLS 1.3 with ECDHE-RSA-AES128-GCM-SHA256 cipher suites. This ensures perfect forward secrecy – even if the server's private key is compromised in the future, past communications remain secure.

mTLS for Internal Services – We enforce mutual TLS between microservices using a private certificate authority, preventing unauthorised services from accessing sensitive APIs.

6.3. Financial Privacy via Discreet Billing Descriptors

To protect users from financial surveillance or judgment, all subscription payments are processed through a gateway that maps the transaction to a neutral descriptor such as `"Ads Boost LTD"` or `"Digital Media Services"`. The user's bank statement never reveals the nature of the service.

This psychological shield is critical for users in conservative environments or those facing relationship scrutiny.

6.4. Mitigating Velocity Fraud and 3DS Failures

We use a Redis-backed token bucket to limit payment attempts per user (e.g., 5 attempts per hour). If a user exceeds this, they are temporarily blocked and prompted to contact support.

For 3D-Secure (3DS) failures, we implement a retry mechanism with exponential backoff, combined with a fallback to alternative payment methods (cryptocurrency via TRC20) to reduce friction.

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7. Performance Benchmarking and Scalability

7.1. Load Testing Methodology

We used distributed load generators (k6 and Locust) deployed across 10 Kubernetes clusters, simulating up to 50,000 concurrent WebSocket clients. Each client sends a new message every 5 seconds, and we measure:

- Time-to-first-token (TTFB) for text
- Time-to-first-audio-chunk
- End-to-end roundtrip latency
- Error rates (HTTP 5xx, WebSocket disconnects)

7.2. Latency and Throughput Results

Metric (p95)	Observed Value
Text TTFB	38.4 ms
Audio First Chunk	84.2 ms
End-to-End WebSocket Roundtrip	94.1 ms
Video Generation (3-sec clip)	3.4 s
Concurrent Sessions (peak)	51,200
Error Rate (non-client)	0.02%

The system sustained the peak load for over 2 hours without degradation, validating our auto-scaling policies.

7.3. Comparison with Commercial Cloud Stacks

Metric	Aimour FlirtGPT Engine	Commercial Cloud LLM + TTS
p95 TTFB	38.4 ms	420.8 ms
p95 Audio First Chunk	84.2 ms	680.1 ms
HTTP 429 / Refusal Rate	0.00%	8.42%
Monthly Cost (per 1M req)	$1.0x (baseline)	14.8x

Our architecture delivers an order-of-magnitude improvement in latency and reliability, primarily due to the elimination of external API hops and the removal of safety guardrail overhead.

7.4. Auto-Scaling and Failover Performance

Kubernetes Horizontal Pod Autoscaler (HPA) scales inference nodes based on GPU utilisation and queue length. When a node exceeds 92% memory usage, the readiness probe fails, draining traffic, and a new node spins up within ~3.1 seconds. Redis Pub/Sub ensures seamless session handover, so clients experience no disconnection.

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8. Operational Excellence: Monitoring, Logging, and Alerting

8.1. Prometheus Metrics and Grafana Dashboards

We expose detailed Prometheus metrics from every service, including:

- Request rates, latencies, and error counts
- GPU utilisation, memory, and temperature
- WebSocket connection counts and event rates
- Queue lengths and inference batch sizes

Grafana dashboards provide real-time visibility and historical trends, enabling rapid anomaly detection.

8.2. Centralized Logging with ELK Stack

All application logs are shipped to an Elasticsearch cluster via Filebeat, with Logstash for parsing and enrichment. Logs are retained for 30 days for forensic analysis.

We use structured logging (JSON) to facilitate querying by session ID, user ID, or correlation ID, making debugging of complex multi-step operations straightforward.

8.3. Anomaly Detection and Proactive Alerting

We deploy machine learning models (e.g., Prophet) on ClickHouse data to predict traffic spikes and proactively scale resources. Alerts are sent to OpsGenie for:

- Sustained latency breaches
- Elevated error rates
- Resource exhaustion warnings
- Security events (e.g., multiple failed auth attempts)

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9. Emerging Agentic Standards and Future Directions

9.1. Model Context Protocol (MCP) Integration

To enable interoperability with other AI agents and tools, we are implementing the Model Context Protocol (MCP) SEP-1649. This exposes a standardised interface for resource discovery, prompt templates, and tool invocation, allowing third-party agents to interact with our FlirtGPT engine in a controlled manner.

9.2. x402 Payment Required for Autonomous Agents

We support the x402 HTTP Payment Required standard, enabling autonomous agents to purchase inference slots via cryptographic micropayments. This opens the door to a marketplace of AI-to-AI interactions, where synthetic companions can collaborate, negotiate, or even entertain each other.

9.3. Roadmap for Enhanced Multimodality

Future work includes:

- Emotion-Aware Voice – Integrating real-time emotion recognition from audio input to adapt the TTS output dynamically.
- Haptic Feedback – Exploring integration with wearable haptic devices to simulate touch and presence.
- 3D Avatars – Deploying real-time 3D character rendering with neural animation, using Unreal Engine 5 or similar.

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10. Conclusion

We have presented the complete architectural blueprint for a high-concurrency synthetic companion platform that achieves sub-100 ms end-to-end latency, supports 50,000+ concurrent sessions, and guarantees zero-knowledge privacy. By decoupling from commercial LLM APIs, aggressively optimising inference with TensorRT-LLM and vLLM, and building a resilient edge-to-database infrastructure, we demonstrate that synthetic companionship can be delivered at scale with superior performance, reliability, and therapeutic integrity.

Our system not only meets the technical demands of real-time multimodal interaction but also aligns with the ethical imperative of preserving user autonomy and emotional safety. As agentic standards mature, we are poised to integrate with the broader ecosystem of autonomous agents, further expanding the possibilities of human-AI co-existence.

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11. Appendix: Configuration Snippets and Code Examples

A. vLLM Engine Initialisation (Python)

```
from vllm import AsyncLLMEngine, AsyncEngineArgs

def initialize_flirtgpt_engine() -> AsyncLLMEngine:
    engine_args = AsyncEngineArgs(
        model="aimour-tech/FlirtGPT-70B-FP8",
        tokenizer="aimour-tech/FlirtGPT-70B-FP8",
        tensor_parallel_size=4,
        gpu_memory_utilization=0.92,
        max_num_batched_tokens=8192,
        max_num_seqs=256,
        quantization="fp8",
        enable_chunked_prefill=True,
        trust_remote_code=True
    )
```

```
    return AsyncLLMEngine.from_engine_args(engine_args)
```

B. Cloudflare Worker Rate Limiter (JavaScript)

```
export default {
  async fetch(request, env) {
    const clientIP = request.headers.get("cf-connecting-ip");
    const { success } = await env.RATE_LIMITER.limit({ key: clientIP });
    if (!success) return new Response("Too Many Requests", { status: 429 });
    // forward request...
  }
};
```

C. FFmpeg Hardware-Accelerated Video Command

```
ffmpeg -y -hwaccel cuda -hwaccel_output_format cuda \
  -i input.raw -i audio.opus \
  -c:v h264_nvenc -preset p1 -tune ll -rc cbr -b:v 3500k \
  -c:a copy -movflags +faststart \
  output.mp4
```

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This report reflects the production architecture as of Q1 2026. All metrics are from internal testing and may vary with deployment specifics. For the latest documentation, please refer to `safe.aimour.ai`